

## REVIEW ARTICLE

**A Review of Face Recognition Techniques**\*S.R Juliet Anesha<sup>1</sup><sup>1</sup>Department of Computer Science and Engineering, C.S.I Institute of Technology, Thovalai, Kanyakumari, India.

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**ABSTRACT**

In today's networked world, the necessity of maintaining information safety as well as preserving the physical property is gradually becoming significant and tedious. As the requirement of high level of security arises, face recognition technology is bound to bend, to cope with the upcoming needs. Also, face recognition has caught the eye of researchers in the areas ranging from image processing and security to computer vision. Streams including content retrieval, network security and video compression get profited by face recognition technology. This is because face recognition deals with people as its centre of attention, thereby increasing the user-friendliness in human-computer interaction. It could also maintain our privacy and protect our assets without dropping our identity. But in this real world environment it seems to be a difficult task because of image variance in terms of position, size, expression and pose. In order to handle all these inter and intra-class variations in face images, various methodologies have been proposed. Here we analyse some methods, their possible strongholds and drawbacks.

**Keywords:** Face recognition, Network security, Video compression, Content retrieval, Intra-class variations.

**1. INTRODUCTION**

Human face plays an important role in our social interactions and in conveying people's identity. Using the human face as a key to security, face recognition technology has received a significant attention in the past several years due to its potential for a wide variety of applications in the research fields. The face recognition technology can be divided into two main stages. They are face detection and face recognition. The detection stage is the first stage which includes identifying and locating a face in an image. The second stage is the recognition stage. It includes feature extraction. Early face recognition algorithms use simple geometric models but the recognition process has now matured into a science of sophisticated mathematical representations and matching processes. [1] states that the face recognition is a risky task due to the presence of variations in the test images including illumination, image misalignment, occlusions etc. The

variations in the test images are handled by means of collecting several sets of training images. The Local Directional Number Pattern (LDNP) [2] uses the directional information about face textures. The face image is divided into several numbers of regions and then the local directional feature of each region has been extracted. The extracted features are then concatenated into a feature vector, which is termed as face descriptor. [3] uses Sparse Coding (SC) that could represent a test image with several linear combination of training images. It seeks for the Maximum Likelihood Estimation (MSE), thereby making it much more robust to the outliers. The Dictionary Learning Method (DLM) [4] is used to learn the action attributes which combines the class distribution and appearance information about the test images. It highlights a Gaussian Process Model (GPM) for sparse representation. Dictionary learning for sparse coding provides a Latent Dictionary Learning method (LDL) [5], which provides an optimal

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solution based on the sparse coefficient generated for the dictionary atoms. Each dictionary atom is jointly learned with a latent vector, which associates the atom to the representation of different classes. The sparse representation based face recognition method supports optimal discrimination of classes in order to achieve good representation power.

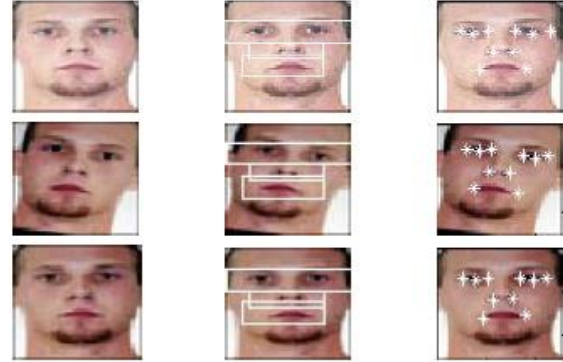
## 2. OVERVIEW OF FACE RECOGNITION

Face recognition is attracting much more attention in the society of network multimedia information access. It is a multidisciplinary activity that contributes in many real world applications like surveillance, criminal investigation, security, verification and authentication of a person. Face has been recognized by comparing the probe image with the gallery dataset. [6] involves the process of matching two face images of different modalities. Gallery database may consist of several images of different subjects, while the prototype subjects consist of images in each modality which includes both the probe image as well as the gallery image. The method compares the similarity of given image with the prototype images from the corresponding modality. This method works well for the scenarios including forensic sketch to photograph, thermal to photograph, near infrared to photograph, etc. [7] Illumination pre-processing is an effective method used in handling the lighting variations in face images. Virtual views of a person under different poses and illumination from a single face image and some set of training samples are used to classify the probe face image. The output of illumination pre-processing method is still a face image, where various feature descriptors are used. It includes Gabor feature and Local Binary Pattern (LBP).

### 2.1. Gabor feature

Gabor feature is an effective way of representing a facial image. [8] highlights the usage of Gabor feature in Linear Discriminant Analysis (LDA). Here the first step is to locate the feature points and then Gabor filters are applied at each point in order to extract a set of Gabor wavelet coefficients. The feature points are determined by a mask generated from a set of training images by means of principal component analysis method [9]. The dimensions of Gabor feature vectors are reduced by using the principle component

analysis method. [10] Localizes the mouth, eyes as well as nose points to obtain the facial features. Thus the face can be represented with its own Gabor coefficients. The Gabor coefficients are expressed at their fiducial points including the points of eyes, mouth and nose. It is illustrated in figure 1.



Adapted from [10]

Figure 1. Facial feature localization

### 2.2. Local Binary Pattern (LBP)

Local binary pattern [11] is used to describe ordinary textures. A face can be seen as a composition of micro textures depending on the local situation. It is also useful for face description. The LBP descriptor consists of a global and a local texture representation. In local texture representation, the face area is divided into several numbers of small regions from which Local Binary Pattern (LBP) histograms are extracted to describe the local features of a face image whereas the global texture is used for discriminating the most non-face objects (blocks), which provides specific and detailed face information that can be used not only to select faces, but also to provide face information for recognition. Both the results will be concatenated into a spatially enhanced featured histogram. [12] states that the histograms of two face images are used as a discriminative feature for intra/extra-personal classifications, that would result in the representation of face images in an effective manner.

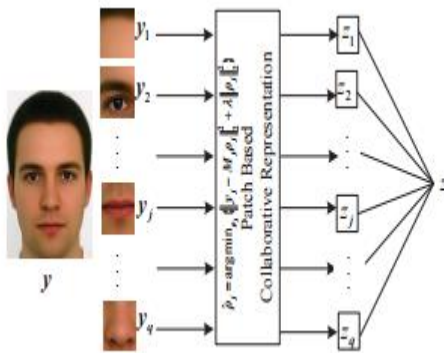
## 3. FACE RECOGNITION METHODS

There are different types of worthy techniques for handling and recognizing face images. Some of the schemes that are used in face recognitions are geometrical local feature based schemes, holistic template matching based systems and hybrid schemes. On the

basis of the particular requirements of a specific task, a suitable scheme must be chosen.

### 3.1. Collaborative Representation based Classification (CRC)

The performance of appearance based face recognition methods, such as the classical eigen face, Fisher face, LPP and the variants of them [13] worsens much with the decrease in training samples. Hence [14] provides a collaborative representation based classification method for improving the face recognition efficiency. Here the input query is divided into several numbers of small local patches [15] for learning the discriminative features of the image. Local patches are extracted from under-sampled training data which contains only restricted information used for classification, while the optimal patch size of input query image varies with training sample size and databases. [16] combines the recognition information of each and every local patches that are on different scales to achieve effective recognition.



Adapted from [16]

Figure 2. Patch based collaborative representation for face classification

Figure 2 illustrates that the query image  $y$  is divided into several local patches as  $y_1, y_2, \dots$ , from where the local features are extracted and are finally concatenated as  $z$  to obtain better recognition of the face image.

### 3.2. Adaptive Discriminant Learning (ADL)

[17] Feature is a term used to represent the input variable or an attribute. Selecting a low dimensional feature subspace from a bundle of features is very crucial for optimal classification. Wrong features selection would degrade the performance of face recognition. The Adaptive Discriminant Learning (ADL)

method [18] combines the process of feature extraction to overcome the Single Sample Per Person (SSPP) problem [19]. The framework obtains an accurate within-class scatter matrix for the single sample through least square regression from the samples of all subjects in the generic set. Also it exploits the Fisher Linear Discriminant analysis (FLD) [20] to learn an adaptive discriminant model with the estimated within-class scatter matrix and the actual between-class scatter matrix of the single sample set. First, the within-class scatter matrix is inferred from the single sample by leveraging an auxiliary generic set and then the between-class scatter matrix is directly calculated from the single sample set. Finally the FLD model is achieved by applying the singular value decomposition on the inferred within-class scatter matrix and the actual between-class scatter matrix. Figure A1 shows the adaptive discriminant frame work.

### 3.3. Extended Sparse Representation-Based Classification (ESRC)

Sparse representation based classification [21] is the basic approach that seeks a representation of the query image in terms of the over-complete dictionary and then performs the recognition by checking which class yields the least representation error. Sparse representation considers all possible supports and adaptively chooses the minimal number of training samples required to represent each test sample. But [22] applies an intra-class variant dictionary to represent the possible variations between the training and the testing images. The dictionary atoms typically represent intra-class sample differences computed from either the gallery faces themselves or the generic faces that are present outside the gallery.

The recognition results of extreme sparse representation based classifier are determined by learning the AR database [23]. The AR database consists of almost 4,000 frontal face images of 126 individuals. The images in the database are taken under different variations, including illumination, expression and facial occlusion/disguise. It also consists of a gallery having only one face image of a person for further recognition. All the images in the AR database are first converted to grey-scale and then cropped to  $165 \times 120$  pixels. The AR database was implemented to test the performance of a

system under conditions where there is variation over time, facial expressions and in lighting conditions.



Adapted from [23]

Figure 3.AR database

Figure 3 describes the ideal conditions including

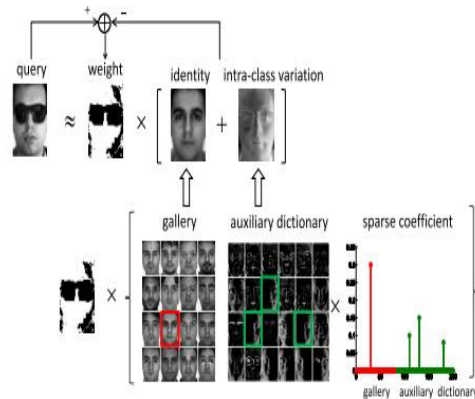
- Facial expressions such as neutral, smile, anger and scream.
- Luminance alterations include left light on, right light on and all side lights on.
- Occlusion modes such as sunglasses and scarf.

AR database addresses the problem of facial expressions and contiguous occlusions. Thus the generalization ability of ESRC is high when dealing with variable expressions, illuminations, disguises and ages.

### 3.4. Robust auxiliary dictionary learning

[24] addresses the problem of under-sampled face recognition by learning the Robust Auxiliary Dictionary (RADL). The dictionary learning could handle the corrupted images due to occlusions or disguise by learning the images from the subjects not of interest. [25] Auxiliary dictionary is constructed from the external data with subjects not of interest. With the observed auxiliary dictionary, one can have one or very few images per person as that of training dictionary, i.e. it might consist of the face images relevant to the input query image, whereas the gallery dataset consists of only one face image for each subject. Hence by comparing both the gallery and the auxiliary dictionary, it is possible to handle the images with large intra-class variations including illuminations, expressions, occlusions, etc. The corrupted image regions of the input query can

be automatically disregarded by learning an auxiliary dictionary from an external dataset together with robust sparse coding.



Adapted from [25]

Figure 4.Undersampled face recognition using RADL

Figure 4 illustrates the working of auxiliary dictionary learning and robust sparse coding [26] in a unified optimization framework. Framework includes a gallery set that contains one or few face images per subject of interest, while the auxiliary dictionary is learned from the external data for observing possible intra-class image variants. For the input query image, a weight [27] has been generated and then the query image is compared with the images in the gallery set and in the auxiliary dictionary. Based on the comparison result, a sparse coefficient has generated. Thus the identity image with minimum reconstruction error from the gallery and an intra-class variant image from auxiliary dictionary are obtained. Finally it was concatenated and the optimal solution is compared with the weight of the query image.

The presence of emotions in the query image is detected by using an Extreme Sparse Learning (ESL) method [28] which uses a spatio-temporal descriptor to handle the pose invariant features. The spatio-temporal descriptor has been generated by means of concatenating the spatio-temporal features including facial expansion and contraction, local spins around the axis of facial muscles, projections, rotations etc. It combines the task of extreme sparse learning machine [29] and sparse representation in a unified approach. With the minimum reconstruction error obtained for an image, optimal solution [30, 31, 32, 33] has been generated and compared



with the gallery image so that the resultant target image would be effectively recognized and retrieved.

#### 4. CONCLUSION

Face recognition systems used today work very well under constrained conditions by handling all such intra-class variations including illuminations, expressions, emotions as well as the pose invariant features. To deal with single sample per person (SSPP) problem, earlier face recognition technologies use patch based classification methods. With this method, the input query image has been divided into several numbers of local patches and later they are concatenated into a single image. But it won't support the images with large intra-class variations. Sometimes it may also lead to the mismatch of images. In order to overcome such a situation, sparse representation based classification methods has been proposed but it handles only the corrupted face images due to occlusion or disguise. Later the intra-class variations and the occlusions are handled well by learning both the auxiliary dictionary and sparse coding in a unified approach. Spatio-temporal descriptor used in the extreme sparse learning method plays a major role in handling the emotions and pose invariant features. Even though all these variations are handled well, face recognition algorithms sometimes fail under vastly varying conditions. Next generation person recognition systems will have to recognize people in real-time and in less constrained situations so that the most potential technique should be designed for wide-spread applications.

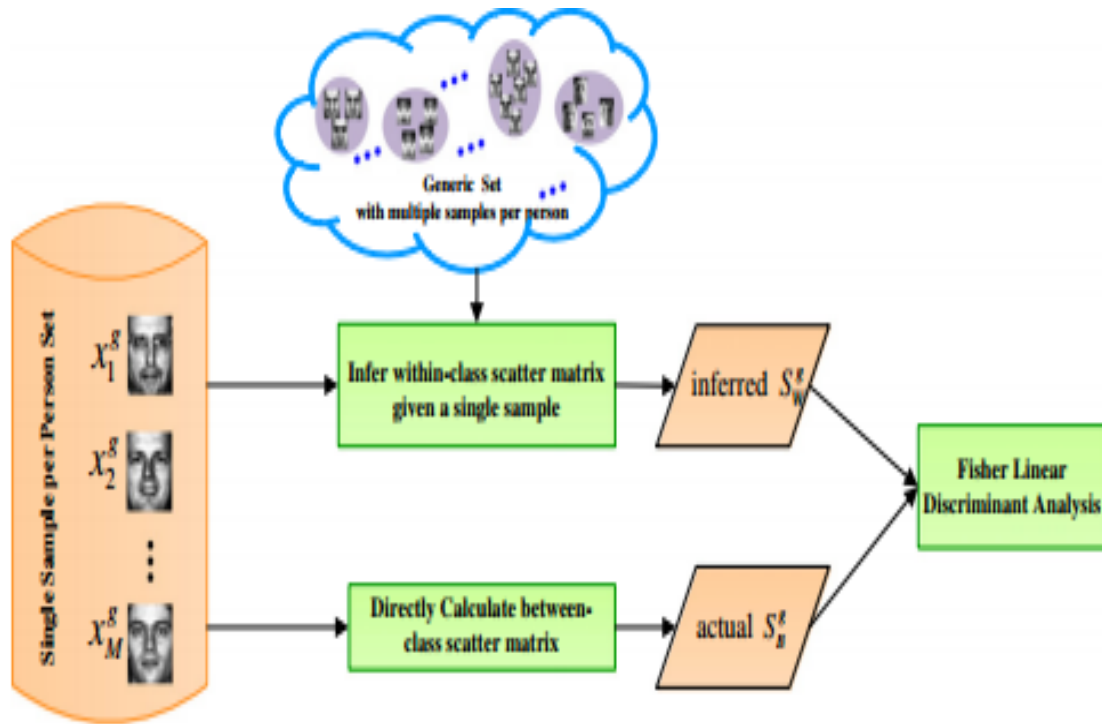
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APPENDIX A



Adapted from [18]

Figure A1. Adaptive Discriminant Framework